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ABSTRACT

Detection, tracking and classifying vessels of all sizes approaching ports and harbors is an imperative aspect to the security of complex maritime systems. This case study is an application of the passive acoustic method for vessel classification. The analysis of noise radiated by passing boats in Hudson River provides sound signatures and specific acoustic features of various boats. The features are then implemented into a decision-making algorithm used for final classification.

INTRODUCTION

Marine transportation plays a vital role in the global economic viability of the United States. As a maritime nation, the United States depends on a strong commercial maritime industry that is tied to maritime security and its stability. Ports and affiliated transportation are all part of a complex system and are potential targets, with wide-scale disaster implications. A need to detect, track and classify vessels of all sizes approaching our ports and harbors is imperative to the security of this country and its complex maritime systems. This case study is an application of the passive acoustic method for vessel classification. The complexity of the classification problem is approached using acoustic signature analysis. Prior studies at Stevens Institute of Technology found that reliable results can be obtained based on signal frequency analysis, specifically, some of the most useful signal characteristics are found in the signal's envelope spectrum. Detection of Envelope Modulation on Noise (DEMON) tool is used in this case study to analyze the acoustic signatures of various vessel types and to provide for specific features that are later implemented into a decision algorithm, which determines the final classification.

BACKGROUND

ACOUSTICS

Acoustics involves the study of the production, propagation, and reception of sound. As sound travels through water, the waves attenuate, which enable instrumentation to record the changes and associate them with vessel noise characteristics. The main sources of noise generated by a marine vessel are (1) mechanical noise of the main engine and auxiliary machine, (2) propeller cavitations noise, and (3) hydrodynamic noise of the moving vessel.[1] The acoustic signature produced by the radiating noise consists of a continuous broadband spectrum and line spectrum. It is the specific configuration of the narrow band frequencies that helps classify and identify different classes of vessels.

CLASSIFICATION ALGORITHMS-DECISION TREE

The classification objective is to identify vessels (ferry, speed boat, sail boat etc) based on a training set of acoustic signatures whose group-label is previously known and then be able to embrace any new observation. The general process of classification is placing individual vessels into groups labeled based on quantitative information of their attributes. Attributes are: an in-depth and structured set of categories that are usually denoted by a numerical code. In essence, the attributes are the preparation for the classification algorithm construction. A wide range of classification algorithms has been studied in various fields, some of which have been applied to acoustic signature classification. Common classification algorithms mentioned in acoustics studies are: neural networks, K-nearest neighbors, Gaussian, and decision tree. Due to its simplicity and ability to handle a mix type data set, the decision tree model was chosen as the classification algorithm for this case study. The decision tree uses relative entropy or Kullback-Leibler (KL) to study the contrast between two or more probability vectors. This approach sprung from information theory.[2] A typical decision tree encodes in a form of tree, where data passes through branch like nodes, constructed from the attributes-rule mentioned earlier and eventually flows through to the final leafs representing the group label (ferry, sail boat, speed boat etc). The node selection is accomplished by selecting the attribute that divides the inhomogeneous data into minimal inhomogeneous subsets using entropy calculations (Kullback-Leibler method).

METHODOLOGY

DATA COLLECTION

Stevens Passive Acoustic Detection System is composed of four ITC-6050C hydrophones manufactured by International Transducer Corporation and connected to an underwater computer, which communicates and feeds acoustical information (both acquisition and analysis) into the control room of the Maritime Security Laboratory (MSL) at Stevens Institute of Technology (figure 1a).

(a)

(b)

Figure 1. (a) picture of the system of the deck of RV Savitsky prepared for deployment and view of the test site (b) with hydrophone position shown by red circle.

This deployment of the acoustic system was initiated in part at the Summer Research Institute program of Stevens University, July 2010. The underwater computer and hydrophones were dropped into the Hudson River approximately 300 ft off the Hoboken NJ shore (Fig.1b.). The database collected during the summer of 2010 is composed of acoustical events of approximately 950 ships accompanied by pictures, video and a manual log record of environmental conditions.

DATA PROCESSING

The task of marine vessel tracking and signature extraction is achieved by using cross-correlation processing of acoustic signals that are detected off four underwater hydrophones. As the vessel noise radiates through the water, it reaches each hydrophone at a different time. The time delay between the hydrophones is the determining factor that allows the system to detect the direction of the moving vessel.

We applied DEMON (Detection of Envelope Modulation on Noise) analysis; for ship classification as it is one of the most reliable acoustic means for ship noise detection and classifications.[3] The noise radiated by a ship is modulated at a rate dictated by parameters of the propeller and engine (number of blades and rotational speed). Evaluation of that modulation helps provide information on the ship, such as the shaft rotation frequency, that can be used for ship classification. Stevens has developed software for measurements of the vessel modulation spectra. DEMON analysis construction involves the following algorithm:

1. Measured signal is divided into parts of 1/1000 of a second. In our case, since the signals were measured at 200 kSamples/sec these parts contain 200 measured points.
2. At each part, the measured samples are squared, mean value of the results is calculated, and then square root of the result is computed. Hence out of initial 200 points in each signal part we have received 1 point for further analysis.
3. Some predefined number (e.g. 2048) of these new calculated subsequent points is collected; their mean value is calculated and then subtracted from initial points. The results are analyzed using FFT Power Spectrum.
4. Steps 1-3 are repeated for the rest of the measured signals.

RESULTS

Examples of the recorded DEMON spectra for several boats are presented in Figures 2 and 3.

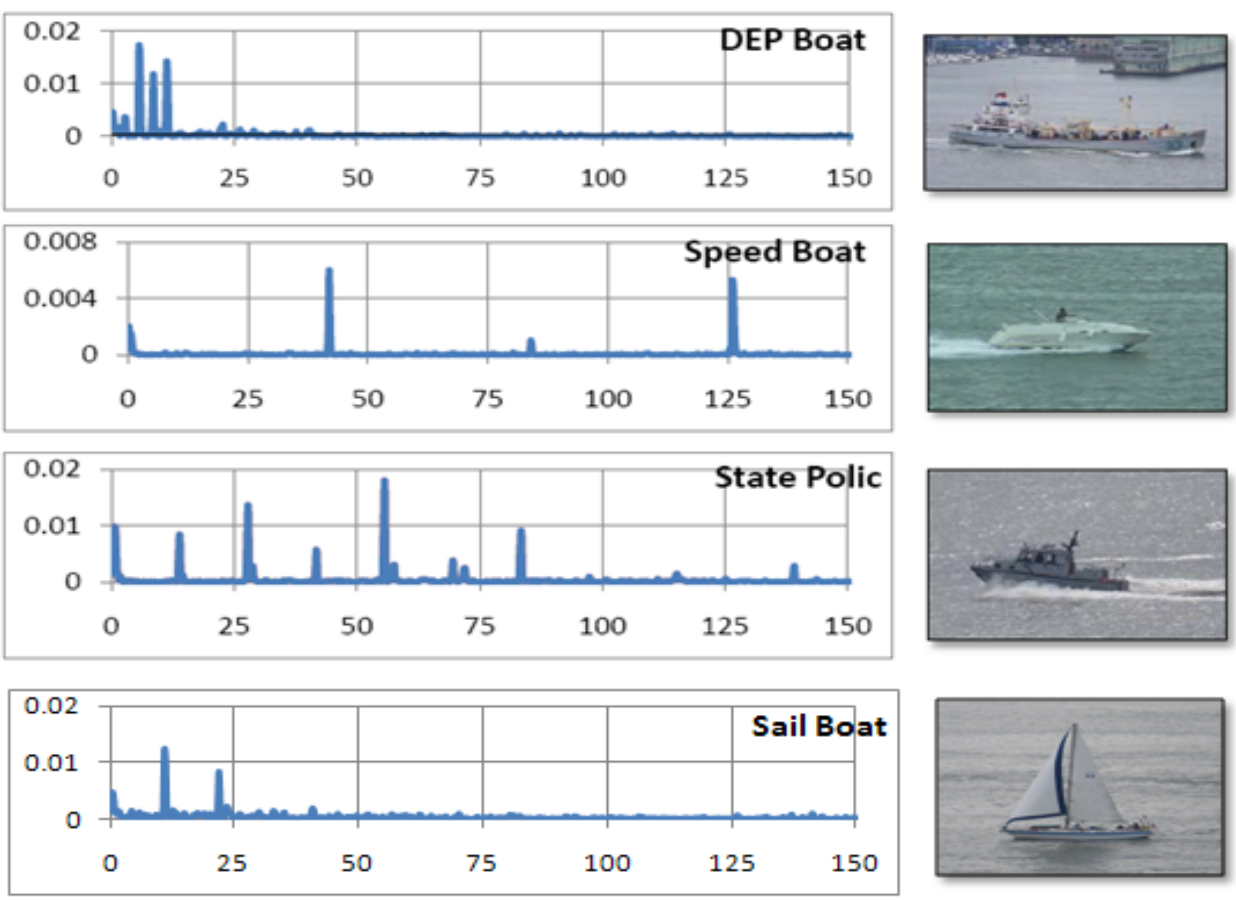


Figure 2. DEMON spectra of various vessels recorded in the Hudson River.

Based on the acoustic signature analysis, the following table provides the attributes and their associated splitting sub-populations that were significant dividers in the classification process:

Attributes	Attributes Subpopulations	Descriptions
Number of Peaks	2-3 peaks	The number of line spectrum that appear on each ocoustic signature
	4 peaks	
	other	
Main Frequency	10-14 Hz	The frequency of the most pronounced spectrum
	41-46 Hz	
	other	
Maximum Frequency	14-41 Hz	The range of the last peaked line spectrum
	Above 130 Hz	
	other	
Amplitude Ratio	2-3 peaks	Ratio of the main frequency versus the second most pronounced frequency
	other	

Table 1. Attributes description and subpopulation values

An example of the attributes extraction of Ferry A and Ferry B is shown in Figure 3 and their attributes values are shown in the Table 2. These observation models allow the classification algorithm to separate and therefore identify the ferries from each other and from all other vessels in the water.

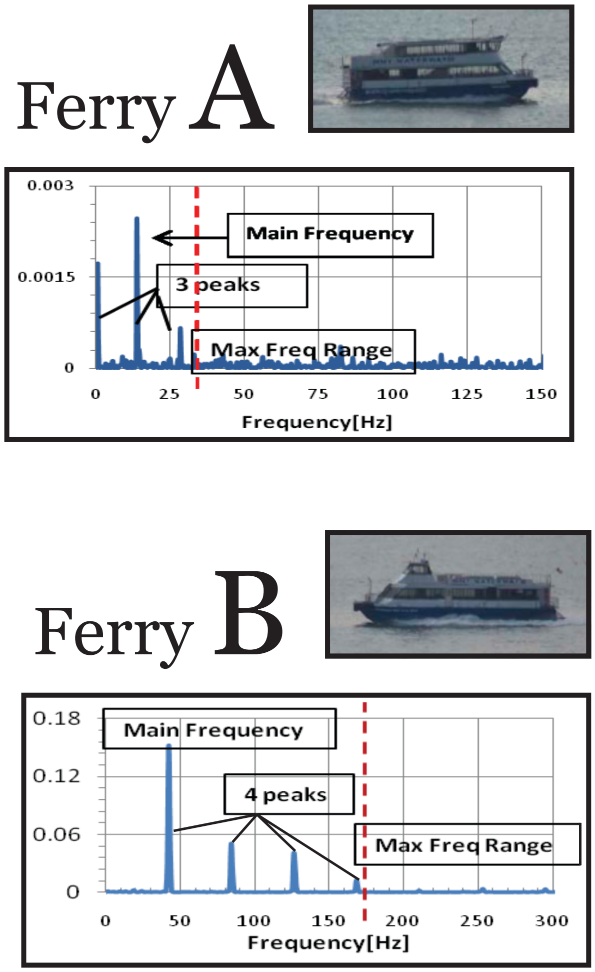
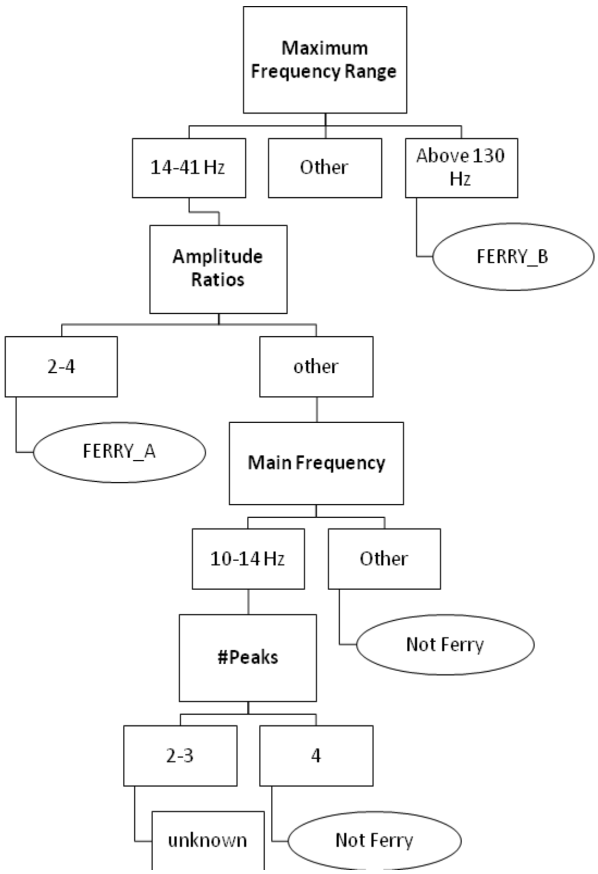


Figure 3. Illustration of the selection diagram for two types of ferries.

Type	# of peaks	Main Freq	Max Freq range	Amplitude ratio
Ferry A	3	~11 Hz	20-40 Hz	2<x<4
Ferry B	4	~ 41 Hz	<130 Hz	2<x<4

Table 2. Attributes values for Ferry A and Ferry B

The following decision tree was constructed from the DEMON signatures of twenty recorded boat sounds based on the calculation of the degree of homogeneousness of the three group labels Ferry A, Ferry B, and Not ferry.



CONCLUSION

This case study has demonstrated the effectiveness of utilizing DEMON acoustic signatures for boat identification. Attributes for classification were extracted from the boat signatures and the simplified decision tree was built. Future work is needed in maintaining a catalog for acoustic signatures; developing a library of few hundred boat signatures will allow for more accurate classification of vessels.

ABOUT THE LEAD AUTHOR

Talmor (Tal) Meir *is a graduate student in ocean engineering at Stevens Institute of Technology. She earned her Bachelor of Science in geophysics from Tel-Aviv University of Israel. At Tel-Aviv University she worked as a research assistant for the Department of Remote Sensing. Her interests include forecast modeling of urban surroundings and the communication and visual interchange of imperative data. In the summer of 2010, Tal took part in the CSR Summer Institute Research (SRI) with a concentration in acoustics for the maritime security domain. Within this context she is currently working on ship classification methods in the metropolitan area of New York City conducted at the Maritime Security Laboratory at Stevens Institute of Technology.*

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